

# An effective anti-forensic contrast enhancement framework using contrast enhancement, histogram smoothening and histogram specification

Mayank Tiwari · Bhupendra Gupta

Received: date / Accepted: date

**Abstract** Recently forensic methods for detection of contrast enhancement (CE) and anti-forensic contrast enhancement methods against such detectors have gained much consideration in multimedia forensics. A few CE detectors investigate the first order statistics, for example, the grey-level histogram uses to decide whether the contrast of given image is enhanced or not. Keeping this in view the end goal to counter these identifiers different anti-forensic systems have been proposed by various researchers. This prompted a method that used second-order statistics of images for CE detection. In this work, we have designed an efficient anti-forensic framework for CE without any type of distortion in both the first and second order statistics of the processed image. The idea of the proposed framework is that we initiate by improve contrast between the given image using any suitable CE method. In the second step, we smooth the histogram of the processed image using some statistical function and finally applying a histogram specification function to map the smooth histogram into the image. Experiments demonstrate that the proposed method adequately overcomes the first and second order statistics based indicators without distorting the quality of the processed image.

**Keywords** anti-forensics · contrast enhancement · quantile based histogram segmentation · histogram smoothening · histogram specification.

## 1 Introduction

Video and image altering has turned out to be progressively simple and advanced, that forgery can be performed without leaving any significant visual traces. It is of most extreme significance for law authorization organizations to validate video/image given as evidence. Analysts in the field of multimedia forensic have proposed different methods ([1]-[4]) to recognize various types of forgeries. Initially the research was more precisely focused on the detection of forgeries in the double compressed images [2] and videos [5]. These systems accept that if an image is compressed twice, it may be altered. This assumption is excessively generic and research recently started by focusing on signal processing operations as opposed to double compression detection.

Principally image CE methods [6] are used after image forgery operation. Because image CE improves the visual nature of the image or potentially hides the traces left by the forgery task. The image CE activities incorporate filtering tasks, for example, low pass and high pass filtering [6]. It additionally incorporates CE for example, Gamma Correction (GC) and Histogram Stretching (HS) [7]. Nonetheless, the enhancement operations also leave some traces on the enhanced images. These are traced by various researchers of the forensic field to identify such pernicious activities [6]-[9]). Distinguishing these enhancements include deciding the unremarkable realistic changes in the images caused by these activities [10]. As of late, anti-forensic techniques are being produced, that play out these enhancements

---

Mayank Tiwari  
Department of Mathematics, PDPM Indian Institute of Information Technology, Design & Manufacturing Jabalpur, MP, India 482005  
Tel.: +91-8827778414  
E-mail: mayanktiwarigits@gmail.com

Bhupendra Gupta  
Department of Mathematics, PDPM Indian Institute of Information Technology, Design & Manufacturing Jabalpur, MP, India 482005  
Tel.: +91-9425155354  
E-mail: gupta.bhupendra@gmail.com

(or the forgery itself) sharply by hiding the traces of enhancement or image forgery [11]. This line of research has picked up significantly as it calls attention to the imperfections and breaks out clauses in forensic algorithms prompting more strong strategies.

In this work, we have focused on developing an anti-forensic CE framework. Numerous strategies have been proposed to distinguish CE in images utilizing first order statistics (FOS). For instance, Stamm *et al.* [10] and [12] proposed a method to detect CE in digital images based on gap and peaks on the histogram, generated by the CE method. In [13], the authors appraise whether an image is CE and recreate the input image. Other histogram based CE indicators include [14].

A considerable number of anti-forensic techniques have been proposed against such FOS based CE finders. For instance, in [21], Cao *et al.* developed a neighborhood random dithering in the essential mapping of CE to keep away from peaks and gaps in the histogram of the processed image. Likewise, Kwok *et al.* in [22] utilize Internal Bit Depth Increase strategy to expand the precision in keeping away from peak and gap antiques. Additionally, Barni *et al.* in [11] proposed a universal anti-forensic method to counter histogram based manipulation indicators. Alfaro *et al.* in [23] propose a general assaulting strategy utilizing a single target function against histogram based finders. Cao *et al.* in [24] propose track forging and track hiding against CE indicators. In [25] Ravi *et al.* proposed a method for anti-forensic CE of all type of images. Ravi *et al.* formulated an optimization problem using a variant of the well-known Total Variation (TV) norm image restoration formulation.

Since FOS based CE identification procedures are appeared to be less robust by the previously mentioned anti-forensic methods [7], CE indicators in light of different measurements were proposed. Authors in [26] utilized the internal channel dependency as a result of color image interpolation to distinguish CE. Essentially, a method proposed by Rosa *et al.* in [7] takes a gander at the Gray Level Co-occurrence Matrix (GLCM) of an image to decide if it is CE or not. This uses second order statistics (SOS) of the image and it appeared to be compelling against anti-forensics strategies focused on histogram based indicators.

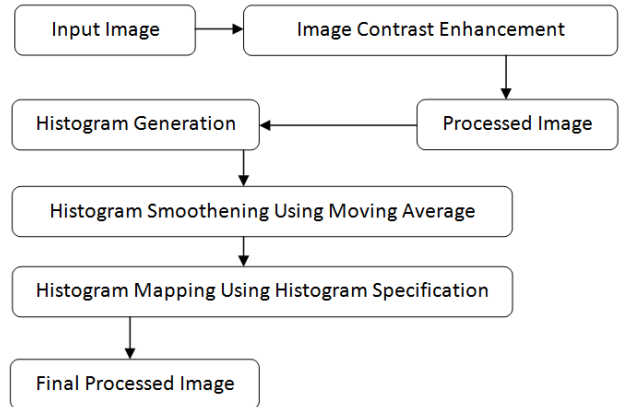
In this work, we have proposed an anti-forensic CE framework. The proposed framework performs CE on an image by applying a suitable CE method. For this, we have tried with different CE methods and selected GC and linearly quantile separated histogram equalization (LQSHE) [15] methods. Though the proposed framework can be well tested on the GC method only, the reason behind the selection of LQSHE method is to

show that the histogram equalization based methods can also be transformed to anti-forensic CE method. After performing CE the next step of the proposed framework is to smooth the histogram of the enhanced image by any statistical histogram smoothing method. For this, we have chosen the moving average filter [17]. At last the proposed framework performs reversed mapping from the histogram to the image by using the histogram specification method discussed in [18]. The proposed framework produces images that have histogram and GLCM as a un-enhanced natural image. This degrades the performance of the SOS detector. We perform extensive experiments on a large database to evaluate the performance of the proposed technique against detector [7].

## 2 The Proposed Method

The framework of the proposed method has been shown by the flowchart in Fig. 1. As discussed earlier that for CE we have selected two methods GC and LQSHE. These two methods are not able to provide anti-forensic CE. However, as we will show in this section that the proposed anti-forensic framework gives this capability to these methods. We named the new methods as *ACE\_GC* and *ACE\_LQSHE*.

Next we are going to explain each step of the proposed anti-forensic CE framework in detail.



**Fig. 1** shows flowchart of the proposed method.

### 2.1 Linearly Quantile Separated Histogram Equalization (LQSHE)

This method was developed by Tiwari *et al.* [15] and later generalized by Gupta *et al.* [16]. Based on results

discussed in [15]-[16] this method performs maximum CE with sufficient brightness preservation. In [15] authors have shown that this method does not use recursive segmentation of histogram and hence it achieves better speed as compared to many other methods. Also as the segmentation of histogram is a linear function so we can gain any level of CE, which is otherwise not possible by other CE methods.

## 2.2 Gamma Correction (GC)

Gamma Correction is an important but seldom understood the character of virtually all digital imaging systems. It defines the relationship between a pixel's numerical value and its actual luminance. Without gamma, shades captured by image capturing device wouldn't appear as they did to our eyes (on a standard monitor). It is also referred to as gamma correction, gamma encoding or gamma compression, but these all refer to a similar concept. Mathematically GC is performed is an image  $I$  as:

$$Y = \left\lceil 255 \cdot \left( \frac{I}{255} \right)^\gamma \right\rceil, \quad (1)$$

where  $Y$  is the processed image by GC method and  $\lceil \cdot \rceil$  is round function. The GC is an important operation in digital image processing and digital camera processing pipeline, since GC redistributes tonal levels closer to how our eyes perceive them, fewer bits are needed to describe a given tonal range. Otherwise, an excess of bits would be devoted to describing the brighter tones (where the camera is relatively more sensitive), and a shortage of bits would be left to describe the darker tones (where the camera is relatively less sensitive).

## 2.3 Moving Average Filter

After performing image CE using GC or LQSHE method. Next we are interested in removing the peaks and gaps generated by these methods on the histogram of processed images. At this point we were looking for a method which satisfies these three criteria:

- The histogram smoothing method must be computationally efficient.
- The different between the two histograms (histogram of processed image and smooth histogram) must be minimum.
- The smooth histogram must have same shape as that of histogram of processed image.

We have tried with many histogram smoothing techniques such as discussed in [17], [19], and [20]. We found

that the moving average filter suggested by Tiwari *et al.* [17] fulfils our all requirements.

Next we are going to provide a detailed description of the moving average based histogram modification filter. Consider  $H$  is the histogram of given image  $I$ . Now the weighted average based histogram modification filter of size  $n$  is given by:

$$H_{wt}[I_k] = \frac{\sum_{j=k-n}^{k+n} H[I_j]}{2n+1}, \quad (2)$$

where  $I_{min} \leq k \leq I_{max}$ . The above equation leads to change in the weights of the  $H_{wt}[\cdot]$ , hence to make the  $H_{wt}[\cdot]$  as a PMF, we need to normalize it:

$$pmf[I_k] = \frac{H_{wt}[I_k]}{\sum_{j=1}^{X-1} H_{wt}[I_j]}. \quad (3)$$

Here one thing to notice that as  $n$  increases, then the  $pmf[I_k]$  will be close to uniform distribution. Mathematically:

$$pmf[I_k] \sim \frac{1}{I_{X-1} - I_0}. \quad (4)$$

Now it is clear that the resultant normalized  $pmf[\cdot]$  (normalized histogram) will be smooth enough and it will be free from gaps and peaks.

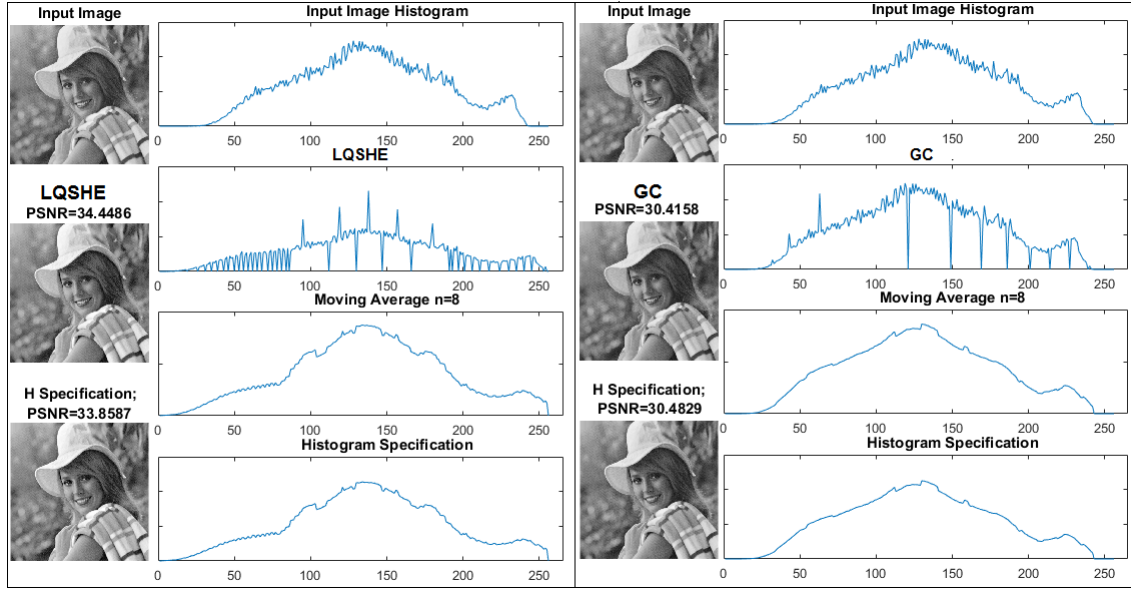
## 2.4 Histogram Specification

The last step is to form the final processed image from the normalized  $pmf[\cdot]$ . For this, we are using the method suggested in [18]. This method is based on the definition of an ordering relation which induces an almost strict ordering on image pixels. Once the order is achieved, pixels are immediately separated into classes and assigned to the desired gray-level. This strict ordering is consistent with the natural one and thus, the information content of images is generally preserved.

Different results generated by the proposed method at different stages have been shown in Fig. 2. It is clear from Fig. 2 that the GC and LQSHE methods are enhancing sufficient contrast in the given image without distorting its features, also the moving average filter smooth the histogram in such a way that the resultant histogram is free from peaks and gaps. At last the histogram specification method maps the histogram in such a way that the resultant image has almost same histogram as the specified histogram, which is free from peaks and gaps.

## 3 Experimental Setup

For quantitative evaluation of anti-forensic nature of the proposed framework, we have used CE detector



**Fig. 2** shows results generated by the proposed method at different stages for famous Elaine image. Here we have used *ACE\_HSQHE* ( $q = 7, n = 8$ ) and *ACE\_GC* ( $\gamma = 1.2, n = 8$ ) methods for CE. (readers are requested to zoom the image in the electronic document as the fine details may not be visible in printed copy.)

discussed in [7] on the images processed by the proposed framework. For doing this we have taken 4000 images from the database [27]. We have considered this database as original database. Then we have created GC database by applying the GC method for different values of  $\gamma \in \{0.6, 0.8, 1.2, 1.4\}$ . Similarly we have created anti-forensic CE (ACE) database by applying method suggested in [25] for  $\gamma = \{0.6, 0.8, 1.2, 1.4\}$ . Next we have created two databases *ACE\_GC* ( $\gamma \in \{0.6, 0.8, 1.2, 1.4\}, n = 10$ ) and *ACE\_LQSHE* ( $q \in \{7, 9, 11, 13\}, n = 10$ ) by using the proposed framework.

## 4 Experimental Results

The framework presented in Section 2 is producing images having sufficient contrast with anti-forensic CE features. As suggested in [7] that the CE detector analyzes the GLCM plot of the processed images. These plots are compared with plots obtained from original images. Hence we are showing the CLCM plot of the famous Lena image with its GC version ( $\gamma = 1.2$ ), the ACE method and the proposed framework with *ACE\_LQSHE* and *ACE\_GC* methods. The CLCM results have been shown in the third column of Fig. 3.

It can be clearly seen that the empty rows and columns introduced by the LQSHE and GC methods are filled by the proposed framework in a GLCM which is quite similar to that of the original. Also, the corresponding images from which the GLCMs were obtained are given in the first row. It can be seen that the images

produced by ACE and the proposed framework are very similar to the input image.

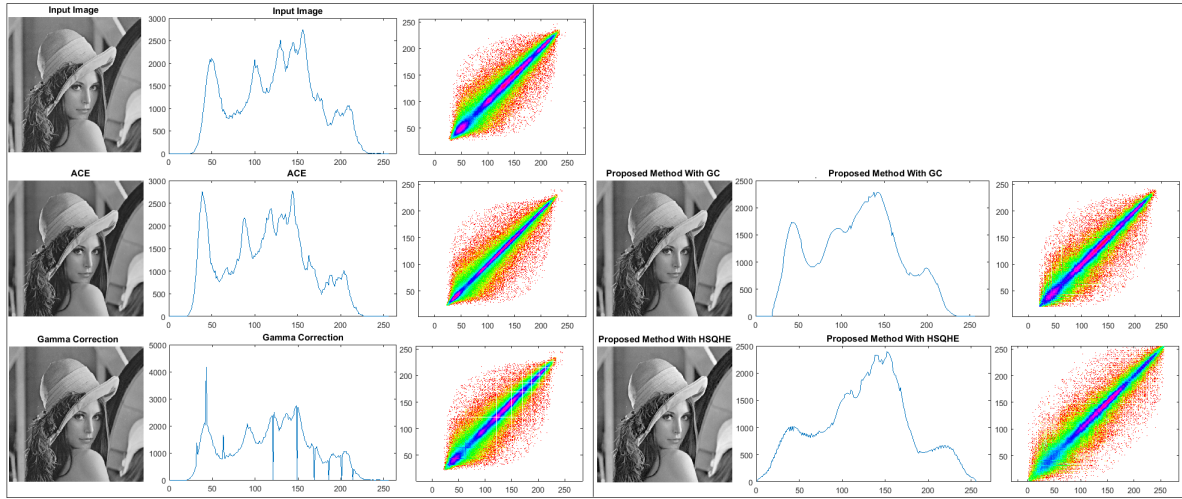
The second column in Fig. 3 shows the gray level normalized histograms of the original, GC, ACE and the *ACE\_LQSHE* and *ACE\_GC* images. It can be clearly seen that the histogram of the ACE and the proposed method's images look very much similar to that of the original. The *ACE\_LQSHE*, *ACE\_GC* and the ACE algorithm perform CE on an image without introducing peaks and gaps in its histogram or empty rows and columns in its GLCM.

In Table 1, we are showing the results of the average peak signal to noise ratio (PSNR) values for all 4000 images used in our work. PSNR is used to measure the amount of CE in the processed images [15]-[17]. We observe that the highest average PSNR values are obtained by the *ACE\_HSQHE* method.

**Table 1** Average PSNR Values for All 4000 Images

Methods	$\gamma = 0.6$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 1.4$
GC	16.41	23.62	25.73	20.64
ACE	16.96	24.12	28.03	23.07
ACE_GC (n=10)	19.49	23.82	23.11	16.46
Methods	$q = 7$	$q = 9$	$q = 11$	$q = 13$
ACE_HSQHE (n=10)	33.71	34.66	35.16	35.58

Next in Table 2 we are showing results of average TPR [in round(%)] for all 4000 images using the CE detector discussed in [7]. For calculation of these results, we have carefully checked GLCM plots of each image produced by different methods. Now the TPR is cal-



**Fig. 3** shows results of GLCM for different methods on the famous Lena image. Here parameters are set as for GC  $\gamma = 1.2$ , AGC  $\gamma = 1.2$ ,  $ACE\_GC$   $\gamma = 1.2$ ;  $n = 10$ , and  $ACE\_HSQHE$   $q = 7$ ;  $n = 10$ .

culated as the total number of images those have their GLCM plots as same as un-enhanced images.

**Table 2** Average TPR [in round(%)] for All 4000 Images Using The CE Detector Discussed in [7]

Methods	$\gamma = 0.6$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 1.4$
GC	10	10	10	10
ACE	65	87	87	87
ACE_GC (n=10)	93	93	93	93

Methods	$q = 7$	$q = 9$	$q = 11$	$q = 13$
ACE_HSQHE (n=10)	90	90	90	90

From Table 1 and 2 we can observe that the proposed framework is capable of converting any CE method to anti-forensic CE method. The proposed framework works the best for the HSQHE method, as for this method its corresponding anti-forensic CE method  $ACE\_HSQHE$  produces images with sufficient contrast also it has good TPR. However the GC method its corresponding anti-forensic CE method  $ACE\_GC$  has good TPR but it fails to get good PSNR values. However, in either case, the proposed framework is successfully converting CE methods to anti-forensic CE methods.

## 5 Conclusion

We propose an effective anti-forensic CE framework using CE, histogram smoothing, and histogram specification. The proposed framework performs efficiently against second-order [7] based CE detectors. The resulting image's visual quality is high as indicated by the PSNR values in the experimental section. The efficiency of the approach in degrading the performance of

the second-order CE detector [7] is very high. In the future, the proposed framework can be improved in many ways such as:

1. For CE, any other global or local CE methods can be used.
2. Histogram smoothing using moving average filter can be replaced with any other technique.

## Acknowledgement

We thank [7] and [25] for sharing their MATLAB code with us. We also thank [27] for providing free access of BOSSbase 1.01 database.

## References

1. V. Christlein, C. Riess, J. Jordan, C. Riess, and E. Angelopoulou, "An evaluation of popular copy-move forgery detection approaches," *IEEE Trans. Inf. Forensics Secur.*, vol. 7, pp. 1841-1854, Dec. 2012.
2. X. Lin, J.H. Li, S.L. Wang, A.W.C. Liew, F. Cheng, X.S. Huang, "Recent advances in passive digital image security forensics: a brief review," *Engineering*, vol. 4(1), pp. 29-39, 2018.
3. P. Korus and J. Huang, "Multi-Scale Analysis Strategies in PRNU-Based Tampering Localization," in *IEEE Trans. Inf. Forensics Secur.*, vol. 12(4), pp. 809-824, April 2017.
4. B. Ambili and N. George, "A robust technique for splicing detection in tampered blurred images," *2017 International Conference on Trends in Electronics and Informatics (ICEI)*, Tirunelveli, pp. 897-901, 2017.
5. Xu Q., Sun T., Jiang X., Dong Y., "HEVC Double Compression Detection Based on SN-PUPM Feature," *Digital Forensics and Watermarking. IWDW 2017. Lecture Notes in Computer Science*, vol 10431. 2017.

6. H. Ravi, A. V. Subramanyam, and S. Emmanuel, "Spatial domain quantization noise based image filtering detection," in Proc. IEEE Int. Conf. Image Processing, Sep. 2015.
7. A. De Rosa, M. Fontani, M. Massai, A. Piva, and M. Barni, "Secondorder statistics analysis to cope with contrast enhancement counterforensics," IEEE Signal Process. Lett., vol. 22, pp. 1132-1136, Aug. 2015.
8. H. Zeng, T. Qin, X. Kang, and L. Liu, "Countering anti-forensics of median filtering," in Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing, May 2014, pp. 2704-2708.
9. Y. Zhang, S. Li, S. Wang, and Y. Shi, "Revealing the traces of median filtering using high-order local ternary patterns," IEEE Signal Process. Lett., vol. 21, pp. 275-280, Mar. 2014.
10. M. C. Stamm and K.J.R. Liu, "Blind forensics of contrast enhancement in digital images," in Proc. IEEE Int. Conf. Image Processing, Oct. 2008, pp. 3112-3115.
11. M. Barni, M. Fontani, and B. Tondi, "A universal technique to hide traces of histogram-based image manipulations," in Proc. ACM Workshop on Multimedia and Security, 2012, pp. 97-104.
12. M. Stamm and K. Liu, "Forensic detection of image manipulation using statistical intrinsic fingerprints," IEEE Trans. Inf. Forensics Secur., vol. 5, no. 3, pp. 492-506, Sep. 2010.
13. M.C. Stamm and K.J.R. Liu, "Forensic estimation and reconstruction of contrast enhancement mapping," in Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing, Mar. 2010, pp. 1698-1701.
14. G. Cao, Y. Zhao, and R. Ni, "Forensic estimation of gamma correction in digital images," in Proc. IEEE Int. Conf. Image Process., Sep. 2010, pp. 2097-2100.
15. M. Tiwari, B. Gupta and M. Shrivastava, "High-Speed quantile-based histogram equalisation for brightness preservation and contrast enhancement," IET Image Processing, vol. 9(1), (2014), pp. 80-89.
16. B. Gupta, T.K. Agarwal, "Linearly quantile separated weighted dynamic histogram equalization for contrast enhancement," Computers & Electrical Engineering, vol. 62, 2017, pp. 360-374.
17. M. Tiwari, B. Gupta and S.S. Lamba, "Performance enhancement of image enhancement methods using statistical moving average histogram modification filter," In Proceedings of the 2nd International Conference on Digital Signal Processing (ICDSP 2018). ACM, New York, NY, USA, pp. 65-69. 2018.
18. D. Coltuc, P. Bolon and J.M. Chassery, "Exact histogram specification," in IEEE Trans. Img. Proc., vol. 15, no. 5, pp. 1143-1152, May 2006.
19. B. Gupta, M. Tiwari, "Minimum mean brightness error contrast enhancement of color images using adaptive gamma correction with color preserving framework," Optik - International Journal for Light and Electron Optics, vol. 127(4), pp. 1671-1676, 2016.
20. M. Kim and M. G. Chung, "Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement," in IEEE Transactions on Consumer Electronics, vol. 54, no. 3, pp. 1389-1397, August 2008.
21. G. Cao, Y. Zhao, R. Ni, and H. Tian, "Anti-forensics of contrast enhancement in digital images," in Proc. ACM Workshop Multimedia and Security, 2010, pp. 25-34.
22. C.-W. Kwok, O.C. Au, and S.-H. Chui, "Alternative anti-forensics method for contrast enhancement," in Proc. Int. Conf. Digital-Forensics and Watermarking, 2012, pp. 398-410.
23. P.C. Alfaro and F. Perez-Gonzalez, "Optimal counterforensics for histogram-based forensics," in Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing, May 2013, pp. 3048-3052.
24. G. Cao, Y. Zhao, R. Ni, H. Tian, and L. Yu, "Attacking contrast enhancement forensics in digital images," Sci. China Inf. Sci., vol. 57, no. 5, pp. 1-13, 2014.
25. H. Ravi, A.V. Subramanyam and S. Emmanuel, "ACE- An effective anti-forensic contrast enhancement technique," in IEEE Signal Processing Letters, vol. 23, no. 2, pp. 212-216, Feb. 2016.
26. X. Lin, C.-T. Li, and Y. Hu, "Exposing image forgery through the detection of contrast enhancement," in Proc. IEEE Int. Conf. Image Processing, Sep. 2013, pp. 4467-4471.
27. BOSSbase 1.01, Accessed online from 'http://dde.binghamton.edu/download/ImageDB/ BOSSbase.1.01.zip'.